Online Appendices for
Elections under Biased Candidate Endorsements — An Experimental Study

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Contents

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A Equilibrium Analyses for the Experimental Election Game

A.1 Bayesian Nash Equilibria (BNE)

In this appendix we derive the Bayesian Nash Equilibria (BNE) for our experimental election game. Let q_A and q_B be the probabilities that an ex-ante randomly sampled voter votes for candidates A and B, respectively. Given q_A and q_B, the pivotal probabilities of a vote for A and for B, under any fixed electoral size $\mathscr{N}$, are[1]

$$\begin{aligned} Pr[PivA|q_A,q_B] =& \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i} q_A^i \cdot q_B^i \cdot q_O^{\mathscr{N}-2i} \\ &+ \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}-1}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i+1} q_A^i \cdot q_B^{i+1} \cdot q_O^{\mathscr{N}-2i-1} \end{aligned} \tag{A.1}$$

$$\begin{aligned} Pr[PivB|q_A,q_B] =& \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i} q_A^i \cdot q_B^i \cdot q_O^{\mathscr{N}-2i} \\ &+ \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}-1}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i+1} q_A^{i+1} \cdot q_B^{i} \cdot q_O^{\mathscr{N}-2i-1} \end{aligned} \tag{A.2}$$

where $q_O \equiv 1 - q_A - q_B$ is the probability of a randomly sampled voter abstaining, and $\lfloor x \rfloor$ denotes the largest integer that is not greater than x. Suppose k is directly observed, then voters with $v_i > (<) -k$ strictly prefer candidate A (B) and will cast a vote for candidate A (B) if they vote. Since voting is costly, a voter casts her vote only if the expected benefits of voting dominate the costs, i.e., $c_i \leq |k+v_i| \cdot Pr[PivA|q_A,q_B]$ ($c_i \leq |k+v_i| \cdot Pr[PivB|q_A,q_B]$) for $v_i > (<) -k$. To simplify computation, we approximate the probability distribution of individual voting costs c_i by a continuous uniform distribution on $[0,C]$, where $C = 15$. [2]

$$q_A(k) = \frac{1}{6}\sum_{v \in V, v > -k} \min\left\{\frac{|k+v| \cdot Pr[PivA|q_A,q_B]}{C}, 1\right\} \tag{A.3}$$

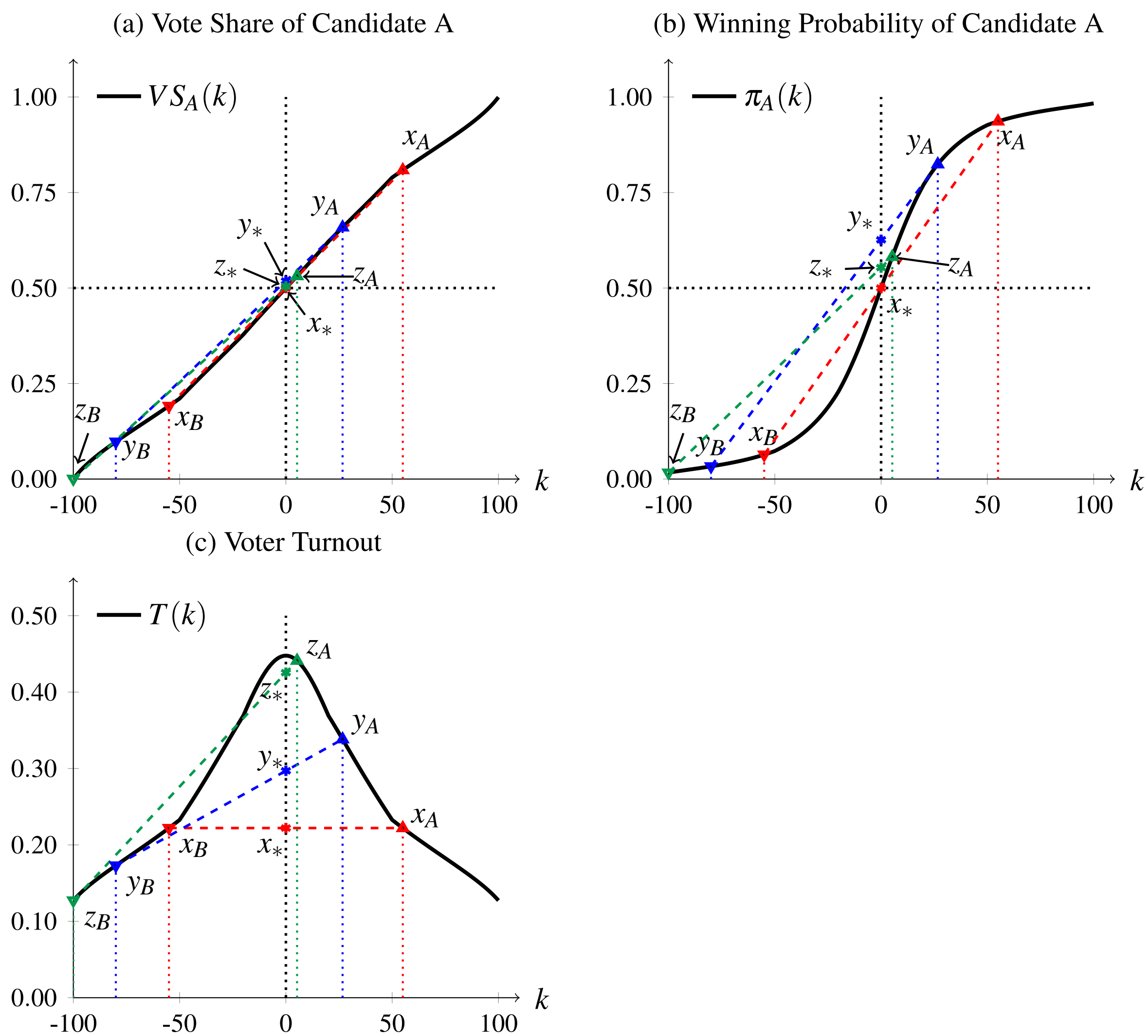
$$q_B(k) = \frac{1}{6}\sum_{v \in V, v < -k} \min\left\{\frac{|k+v| \cdot Pr[PivB|q_A,q_B]}{C}, 1\right\} \tag{A.4}$$

[1] The first term on the right hand side of (A.1) is the probability of tie, and the second term is the probability that candidate A falls exactly one vote behind candidate B, under multinomial distribution (q_A, q_B). In these two cases, a vote for candidate A is pivotal and improves A's winning chance by 0.5. The interpretation is analogous for (A.2).

[2] This continuous approximation is common in the literature. We have also derived equilibria for the case where (as in the experiment) only discrete costs are possible. Though the notation and analysis is more complex, the comparative statics predictions are the same as for the continuous distribution. For ease of presentation, we therefore use the approximation here. All predictions presented in the main text (for example, in Figure 2) are, however, based on the analysis with the discrete cost distribution. More details are available upon request.

where $V \equiv \{-100, -50, -20, 20, 50, 100\}$. The BNE can be obtained by solving the system of equations (A.3) and (A.4), with the pivotal probabilities therein replaced by (A.1) and (A.2). We numerically solve for the BNE under the above parameterization for each value of k considered in this paper. Panels (a) to (c) of Figure A.1 depict candidate A's winning probability ($\pi_A(k)$), expected vote share ($VS_A(k)$), and voter turnout $T(k)$ predicted by BNE as functions of k, respectively.

Figure A.1: Geometric Analyses for the Electoral Impacts of Endorser Bias



Note: Panels (a) to (c) depict candidate A's expected vote share $VS_A(k)$, winning probability $\pi_A(k)$, and the expected voter turnout $T(k)$ predicted by BNE as functions of k, respectively. Endorser's bias increases from $\chi = 0$ (red nodes) to $\chi = 55$ (blue nodes) to $\chi = 95$ (green nodes). In all three panels, w_A, w_B and w_*, $w \in \{x, y, z\}$, represent the corresponding equilibrium outcome conditional on message A, message B and unconditionally (ex-ante), respectively. The dashed line segments represent the sets of all convex combinations of w_A and w_B, for $w \in \{x, y, z\}$.

The interim and ex-ante impacts of endorser bias on candidate A's winning probability can be derived geometrically through Figure A.1b. We start with $\chi = 0$ (UB). From Table 1 in the main text we know that $k_A(0) = 55$ and $k_B(0) = -55$. As a result, candidate A's winning probability conditional on message A (B) equals $\pi_A(55)$ ($\pi_B(-55)$), represented by the red node x_A (x_B). Ex-ante, candidate A's winning probability is a convex combination of $\pi_A(55)$ and $\pi_B(-55)$, and therefore must lie on the red dashed line segment connecting x_A and x_B. By the law of iterated expectations, the posterior means must average back to the prior mean, which is 0. Geometrically, this implies that A's ex-ante winning probability can be represented by the red node x_*, the intersection of segment $x_A x_B$ and the vertical line $k = 0$.

A similar exercise can be done for $\chi = 55$ (WB_A), yielding interim winning probabilities conditional on message A and B represented by the blue nodes y_A and y_B, respectively, and the ex-ante winning probability represented by the blue node y_*. Likewise, for $\chi = 95$ (SB_A) the interim winning probabilities conditional on message A, B and the ex-ante winning probability are represented by the green nodes z_A, z_B and z_*, respectively. The interim impacts of an increase in endorser bias on candidate A's winning probability can thus be straightforwardly captured by the movement from x_s to y_s to z_s, for message $s \in \{A, B\}$. The ex-ante impacts of increasing endorser bias is represented by the movement from x_* to y_* to z_*.

As is evident from Figure A.1b, conditional on either message A or B, candidate A's expected winning probability decreases in endorser bias χ; $x_s > y_s > z_s$ for both $s \in \{A, B\}$.[3] Ex-ante, candidate A's winning probability varies non-monotonically with χ; $y_* > z_* > x_*$. Taken together, these results give rise to Hypothesis 1 formulated in the main text.

The same geometric approach is applied in Figure A.1a to derive the impact of endorser bias on candidate A's expected vote share. Similar to the analysis for the election outcome, we observe that conditional on either message A or B, candidate A's expected vote share decreases in bias χ; $x_s > y_s > z_s$ for both $s \in \{A, B\}$. From the ex-ante perspective, the impact of endorser bias on A's expected vote share is almost negligible; x_*, y_* and z_* are all hovering around 0.5 and are similar in magnitude. As argued in the main text, this is because $VS_A(k)$ is almost a linear function of k and equals 0.5 if $k = 0$. Consequently, variations in A's expected vote share are almost proportional to variations in voters' posterior expectations about k. The latter are invariant from the ex-ante perspective thanks to the law of iterated expectation. For this reason, the ex-ante impact of increasing endorser bias on A's expected vote share is almost negligible.

Figure A.1c presents the impact of endorser bias on voter turnout. Conditional on message A, voter turnout increases in endorser bias ($z_A > y_A > x_A$) while conditional on message B the reverse is true ($x_B > y_B > z_B$). From an ex-ante perspective, we observe that the expected voter turnout increases unambiguously in endorser bias ($z_* > y_* > x_*$). Finally, voter turnout attains its maximum if voters are uninformed; in this case, voters behave as if $k = 0$ is common knowledge. As is evident from Figure A.1c, $T(k)$ is highest when $k = 0$. These results give rise to Hypothesis 2.

[3] It is implicitly understood that whenever we compare nodes in Figures A.1b to A.1c, we are comparing their values on the vertical axis.

A.2 Quantal Response Equilibria (QRE)

In this appendix, we derive the standard quantal response equilibria (QRE; McKelvey and Palfrey (1995)) for our election game. Denote any voter i's expected utility from voting for candidate A, B or abstaining, conditional on diamond allocation k and private type (v_i, c_i), by $EU^A(k, v_i, c_i)$, $EU^B(k, v_i, c_i)$ and $EU^O(k, v_i, c_i)$, respectively. Without loss of generality, we normalize $EU^O(k, v_i, c_i)$ to zero for all i's. With this normalization, we can interpret $EU^\omega(k, v_i, c_i)$ as the difference between the expected utilities from voting for ω and abstaining, where $\omega \in \{A, B\}$. Following the cost-benefit reasoning in Appendix A.1, we have[4]

$$EU^A(k, v_i, c_i) = \frac{(k + v_i) \cdot PivA(k) - c_i}{100} \tag{A.5}$$

$$EU^B(k, v_i, c_i) = \frac{-(k + v_i) \cdot PivB(k) - c_i}{100} \tag{A.6}$$

where $PivA(k)$ and $PivB(k)$ are pivotal probabilities of a vote for candidate A and B, respectively, when k is common knowledge. In contrast to BNE, QRE allows voters to make errors in their voting decisions. This can be modeled by adding a stochastic error term to the expected utilities, which yields:

$$\begin{aligned} &EU^A(k, v_i, c_i) + \frac{\varepsilon_A}{\lambda} \\ &EU^B(k, v_i, c_i) + \frac{\varepsilon_B}{\lambda} \\ &EU^O(k, v_i, c_i) + \frac{\varepsilon_O}{\lambda} = \frac{\varepsilon_O}{\lambda} \end{aligned}$$

where ε_d for $d \in \{A, B, O\}$ denotes i.i.d. noise and $\lambda > 0$ is a parameter that captures the relative weight of noise in the perceived expected utility. In a QRE (for the normal form game), a voter will still choose the action that yields the highest expected utility, but this is now a stochastic event. For example, she will vote for A if $EU^A(k, v_i, c_i) + \frac{\varepsilon_A}{\lambda} > EU^B(k, v_i, c_i) + \frac{\varepsilon_B}{\lambda}$ and $EU^A(k, v_i, c_i) + \frac{\varepsilon_A}{\lambda} > \frac{\varepsilon_O}{\lambda}$ hold simultaneously. Or equivalently, $\varepsilon_B - \varepsilon_A < \lambda \left(EU^A(k, v_i, c_i) - EU^B(k, v_i, c_i) \right)$ and $\varepsilon_O - \varepsilon_A < \lambda EU^A(k, v, c)$. Specification of the distribution functions of ε_A, ε_B, ε_O then yields the probabilities that the voter will vote for A or B, or will abstain. We derive the logit QRE, where ε_d is assumed to follow the extreme value type I distribution for all $d \in \{A, B, O\}$. In this case, the probabilities of choosing each action d, denoted by p^d, are given by:

$$p^A(k, v_i, c_i; \lambda) = \frac{e^{\lambda EU^A(k, v_i, c_i)}}{e^{\lambda EU^A(k, v_i, c_i)} + e^{\lambda EU^B(k, v_i, c_i)} + 1} \tag{A.7}$$

[4] We divide the obtained difference in expected payoffs by 100 to make sure that k, v_i and c_i are all re-scaled to a range between 0 and 1. This is for ease of computation.

$$p^B(k,v_i,c_i;\lambda) = \frac{e^{\lambda EU^B(k,v_i,c_i)}}{e^{\lambda EU^A(k,v_i,c_i)} + e^{\lambda EU^B(k,v_i,c_i)} + 1} \tag{A.8}$$

$$p^O(k,v_i,c_i;\lambda) = \frac{1}{e^{\lambda EU^A(k,v_i,c_i)} + e^{\lambda EU^B(k,v_i,c_i)} + 1} \tag{A.9}$$

Using (A.7) to (A.9), we can compute the probabilities of a randomly sampled voter voting for A and B, $q_A(k|\lambda)$ and $q_B(k|\lambda)$, by

$$q_A(k;\lambda) \equiv E_{v,c}[p^A(k,v,c;\lambda)] = \int_v \int_c p^A(k,v,c;\lambda) d\gamma(c) dG(v)$$
$$q_B(k;\lambda) \equiv E_{v,c}[p^B(k,v,c;\lambda)] = \int_v \int_c p^B(k,v,c;\lambda) d\gamma(c) dG(v)$$

where $G(v)$ and $\gamma(c)$ are the CDFs of private ideology v_i and voting costs c_i, respectively. In our experimental election game, both v_i and c_i are independently drawn for each voter i. v_i follows a discrete uniform distribution $G(\cdot)$ over $\{-100,-50,-20,20,50,100\}$ (denote each element by v^r, $r = 1,2,\cdots,6$), and c_i follows a discrete uniform distribution $\gamma(\cdot)$ on $\{1,2,\cdots,C\}$ (denote each element by c^s, $s = 1,2,\cdots,C$). Parameter C is an integer and it specifies the upper bound of voting costs. Let $\mathbb{P}^d(k;\lambda)$ be a $6\times C$ matrix with the (r,s) element $\mathbb{P}^d_{r,s}(k;\lambda) = p^d(k,v^r,c^s;\lambda)$, for each $d \in \{A,B,O\}$. We can then simplify the above expressions to the following formulas ($\vec{e}_{1\times 6}$ and $\vec{e}_{C\times 1}$ are vectors of ones):

$$q_A(k;\lambda) = \frac{1}{6} \times \frac{1}{C} \cdot \vec{e}_{1\times 6} \cdot \mathbb{P}^A(k;\lambda) \cdot \vec{e}_{C\times 1} \tag{A.10}$$

$$q_B(k;\lambda) = \frac{1}{6} \times \frac{1}{C} \cdot \vec{e}_{1\times 6} \cdot \mathbb{P}^B(k;\lambda) \cdot \vec{e}_{C\times 1} \tag{A.11}$$

The pivotal probabilities, $PivA(k)$ and $PivB(k)$, depend on both $q_A(k|\lambda)$ and $q_B(k|\lambda)$, as well as the electorate size $\mathcal{N}$. These pivotal probabilities can be calculated by the formulas below (based on the multinomial distribution):[5]

$$\begin{aligned} PivA(k) =& \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathcal{N}}{2} \rfloor} \binom{\mathcal{N}}{i} \binom{\mathcal{N}-i}{i} q_A(k;\lambda)^i q_B(k;\lambda)^i q_O(k;\lambda)^{\mathcal{N}-1-2i} \\ &+ \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathcal{N}}{2} \rfloor} \binom{\mathcal{N}}{i} \binom{\mathcal{N}-i}{i+1} q_A(k;\lambda)^i q_B(k;\lambda)^{i+1} q_O(k;\lambda)^{\mathcal{N}-1-2i} \end{aligned} \tag{A.12}$$

[5] (A.12) and (A.13) are obtained from (A.1) and (A.2) by replacing q_d with $q_d(k|\lambda)$ for all $d \in \{A,B,O\}$.

$$
\begin{aligned}
PivB(k) = & \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i} q_A(k;\lambda)^i q_B(k;\lambda)^i q_O(k;\lambda)^{\mathscr{N}-1-2i} \\
& + \frac{1}{2}\sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i}\binom{\mathscr{N}-i}{i+1} q_A(k;\lambda)^{i+1} q_B(k;\lambda)^i q_O(k;\lambda)^{\mathscr{N}-1-2i}
\end{aligned} \tag{A.13}
$$

Equations (A.5) to (A.13) formulate a fixed-point problem and we can solve for the QRE predictions numerically for any pair of k and λ, given model primitives $G(\cdot)$, $\gamma(\cdot)$ and $\mathscr{N}$. Some model primitives are different between our experiments conducted in 2016 and 2017. Specifically, for our 2016 experiment, the upper bound on voting costs C equals 20 and the electorate size $\mathscr{N}$ equals 11. For our 2017 experiment, $C = 15$ and $\mathscr{N} = 25$. In addition, instead of using the strategy method as in our 2017 experiment, in all treatments with a single endorser we released the public messages to voters before they made voting decisions in our 2016 experiment. As a result, for each round of election, we only observed voters' decisions conditional the realized message.

We use the maximum likelihood (ML) method explained in Appendix C to estimate the logit response parameter λ based on the experiment conducted in 2016. The estimated $\widehat{\lambda}$ equals 19.45. We then use this out-of-sample estimate to generate QRE predictions for our experimental sessions in 2017 (cf. Figure 1 in the main text). Similar to the derivation of BNE, these QRE predictions are obtained by replacing k with the rational posterior expectations of k conditional on the public information voters have.

B Additional Experimental Results

In this appendix we present two sets of additional results regarding our experiment.

B.1 The Explanatory Power of BNE and QRE

In this appendix we evaluate the explanatory power of BNE and QRE predictions. To do so, we regress the observed outcomes on their corresponding predictions:

$$Y_{is} = \beta_0 + \beta_1 Pred_{is} + X_s\gamma + Pred_{is} \times X_s\delta + \varepsilon_{is} \tag{B.1}$$

In (B.1), Y_{is} and $Pred_{is}$ are the observed and predicted aggregate outcome (A's vote share, A's winning probability, or voter turnout) of election i in electorate s. X_s is a vector of standardized electoral background variables (average age, fraction of males, and fraction of students major in economics or business) for electorate s. γ and δ are vectors of coefficients for these electoral backgrounds. The error terms ε_{is} are assumed to be independent across electorates (standard errors are clustered at the electorate level). Note that the interaction terms in (B.1) allow for the impacts of theoretical predictions on observed outcomes to be different across distinct compositions of the electorate. We estimate (B.1) for both BNE and QRE predictions. These estimation results are summarized in Table B.1.

Columns (1) and (5) show that BNE predictions alone can explain 72.3% and 58.6% of the variations in candidate A's observed vote shares and winning probabilities, respectively. Columns (9), however, shows that only 6.5% of the variations in observed voter turnout can be explained by BNE predictions. Compared to BNE, QRE explains higher fractions of variations in the observed election outcomes and vote share (cf. columns (3) and (7)), but it explains approximately the same fraction of observed variations in voter turnout (cf. column (11)). Controlling for electoral background variables does not substantially increase the explanatory power of either BNE or QRE predictions for observed vote shares and election outcomes, but does so for voter turnout by 6.2%-points. Therefore, we conclude that BNE and QRE have strong explanatory power for party vote shares and election outcomes, but much less explanatory power for voter turnout.

Finally, we check for learning effects by conducting the same regression (B.1) separately for sub-samples in blocks 1-4, 5-8 and 9-12. We find little evidence of learning for party vote shares and the election outcomes. The explanatory power of BNE (QRE) for voter turnout, however, increases from 3.9% (3.2%) in blocks 1-4 to 10.8% (13.4%) in blocks 9-12. Though these results indicate some learning effects towards the equilibrium predictions, the amount of variation in observed turnout that can be explained by BNE predictions still remains low.

Table B.1: The Explanatory Power of BNE and QRE Predictions

Dep. Variable	Vote Share of A				Winning Probability of A				Voter Turnout			
	BNE		*QRE*		*BNE*		*QRE*		*BNE*		*QRE*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pred	0.713***	0.713***	1.245***	1.245***	0.826***	0.826***	1.138***	1.138***	0.200***	0.200***	0.458***	0.458***
	(0.037)	(0.007)	(0.067)	(0.009)	(0.012)	(0.008)	(0.019)	(0.008)	(0.022)	(0.020)	(0.059)	(0.045)
Age		0.054***		0.098***		-0.004		0.006***		0.034		0.029
		(0.009)		(0.011)		(0.004)		(0.001)		(0.020)		(0.038)
Males		−0.031***		−0.054***		−0.001		−0.002***		-0.008		0.033
		(0.004)		(0.005)		(0.002)		(0.000)		(0.009)		(0.017)
Econ		0.058***		0.109***		−0.006		0.001		0.023		0.034
		(0.012)		(0.014)		(0.004)		(0.001)		(0.024)		(0.045)
Pred × *Age*		−0.115***		−0.203***		−0.029***		−0.051***		0.020		0.027
		(0.010)		(0.015)		(0.005)		(0.007)		(0.031)		(0.068)
Pred × *Males*		0.057***		0.104***		0.003		0.003		0.010		0.070*
		(0.005)		(0.007)		(0.003)		(0.003)		(0.014)		(0.030)
Pred × *Econ*		−0.126***		−0.230***		−0.031**		−0.050***		0.005		-0.024
		(0.011)		(0.016)		(0.005)		(0.011)		(0.034)		(0.077)
Constant	0.134***	0.134***	−0.130***	−0.130***	0.064***	0.064***	−0.055***	−0.055***	0.466***	0.466***	0.339***	0.339***
	(0.019)	(0.007)	(0.033)	(0.009)	(0.004)	(0.003)	(0.002)	(0.001)	(0.017)	(0.015)	(0.030)	(0.027)
#.Obs.	996	996	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008
R^2	0.742	0.753	0.849	0.861	0.649	0.650	0.777	0.779	0.069	0.131	0.068	0.132

Note: Electoral backgrounds are standardized within the sample. Standard errors are clustered at the session level and reported in parentheses. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.2 More Results on Learning Effects

In this appendix we present further results about learning effects in our experiment. To do so, we compare observed election outcomes and voter turnout across rounds separately for the first, second, and third phase of the experiment. Each phase consists of four blocks (covering the four treatments of the experiment) and each block consists of eight elections under the same treatment condition (cf. Figure 3 in the main text). Using this split into three phases, we performed three types of analyses.

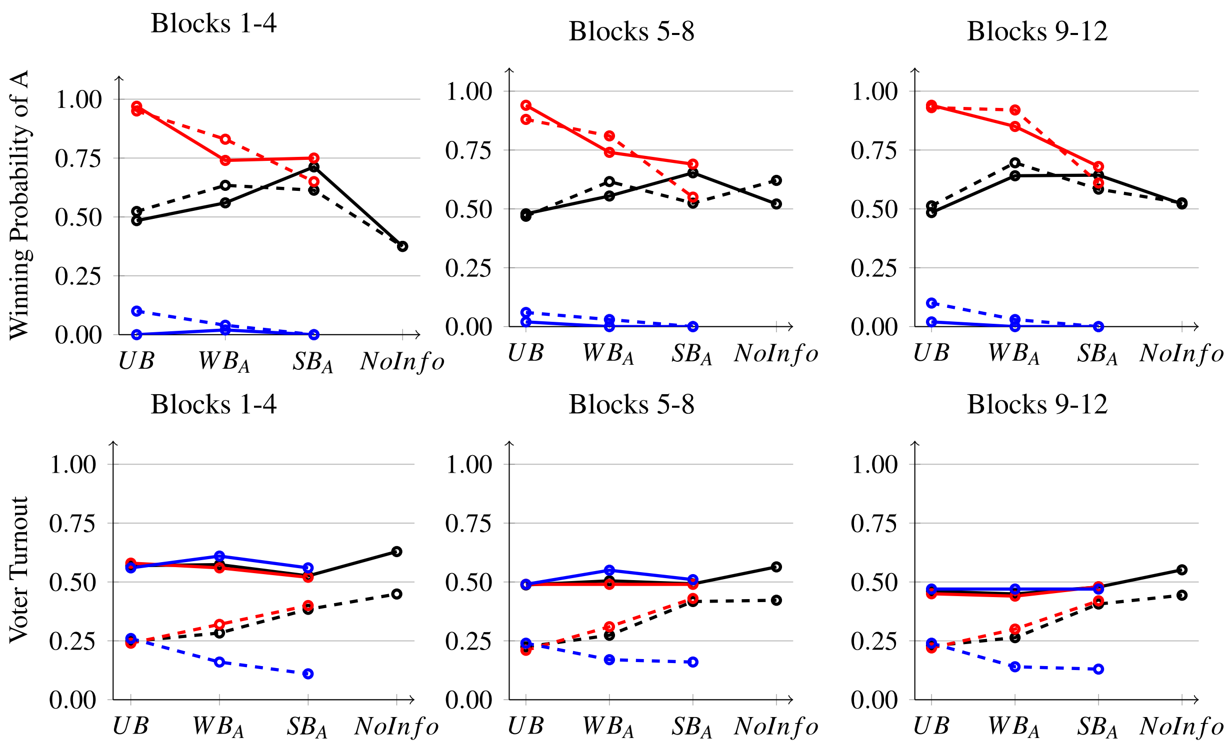
First, we conducted the tests of our hypotheses using data from the last phase only (cf. the last paragraph of Section 6.2). Overall, the analyses show that, rather than voting mindlessly, subjects seem to gain experience and behave more 'rationally' in later blocks; the aggregate turnout rates and election outcomes are closer to the BNE predictions. Learning appears to mitigate the distortion of the election outcome caused by a strongly biased endorsement, driving the observed election outcomes closer to our predicted non-monotonic relationship. Moreover, as explained in the final paragraph of Section 6.2, most conclusions regarding hypotheses testing remain unchanged in the subsample consisting of data from the last four blocks. There are only two exceptions, both in the direction of confirming the comparative statics predicted by our theory.

Second, we considered phase-by-phase the treatment comparisons of winning probability and turnout. The results are presented in Figure B.1. The top panels show how the (interim and ex-ante) observed winning probabilities of candidate A vary over the treatments – and how these compare to BNE predictions – in the different blocks. Consistent with results based on the full sample (cf. Figure 4 in the main text), these charts show that in all stages the election outcome is reasonably well predicted for treatments UB and WB_A.

Substantial deviations from the theoretical (BNE) predictions appear mostly under treatment SB_A and conditional on message A being sent (compare the solid and dashed red lines). As explained in Section 6.1 when discussing Figure 4, the monotonic relationship between A's observed ex-ante winning probability and the endorser's bias is mostly driven by these deviations. As is evident graphically, such deviations are stronger in earlier blocks than later blocks. In particular, the top-right chart suggests that the strictly monotonic relationship between A's ex-ante winning probability and the endorser bias disappears if we focus on data from the last four blocks. This is because in these blocks the observed winning probability under SB_A and message A is much closer to the BNE prediction than before. As a consequence, A's ex-ante winning probabilities are almost identical under WB_A and SB_A (both equal to 0.64; the difference is not statistically different). This suggests again that, if anything, learning tends to push behavior in the direction of our predicted non-monotonicity hypothesis.

The bottom panels of Figure B.1 depict how the (interim and ex-ante) observed turnout rates vary with treatment conditions in different phases. Here we observe partial learning effects. On the

Figure B.1: Aggregate Voting Behavior and Election Outcomes



Note: In all the six panels, the dashed lines depict the electoral outcomes predicted by Bayesian Nash Equilibria (BNE) and the solid lines depict the actual electoral outcomes observed in the experiment. The red (blue) lines denote the interim outcomes conditional on message A (B), while the black lines denotes the ex-ante outcome; the average of interim outcomes weighted by the likelihood of sending messages A and B. We omit QRE predictions in these charts because they are qualitatively similar to BNE predictions.

one hand, turnout substantially drops in later blocks (suggesting that over-voting is mitigated by learning). On the other hand, however, observed (both interim and ex-ante) turnout rates remain largely irresponsive to endorser bias even in the last four blocks. This suggests a persistent deviation that is not easily mitigated by learning. This is one of the results that motivated us to explore alternative behavioral channels explained in Section 7 of the main text.

In our third analysis of the three phases we examined subjects' payoffs (as measured by their expected earnings) in the election. This allows us to determine whether learning helps subjects to better respond to candidate endorsements. Consistent with a positive learning effect, we observe that, for all the four treatments, subjects' average earnings are higher in the last four blocks than across all blocks. This confirms the learning effects we observed above.

C The Hybrid Behavioral Equilibrium Model

In this appendix we formally introduce the hybrid behavioral equilibrium model outlined in the main text and then explain the estimation methods.

C.1 The Formal Model Setup

Let τ denote an *information environment*, which summarizes the public information voters obtain in each treatment. Let Γ be the set of all information environments studied in our experiment:

$$\Gamma = \left\{ NoInfo, (UB,A), (UB,B), (WB_A,A), (WB_A,B), (SB_A,A), (SB_A,B) \right\} \tag{C.1}$$

Our hybrid equilibrium model extends the standard logit QRE model (presented in the previous appendix) in three ways. First of all, for each information environment τ, it allows voters' common posterior expectation about the state, denoted by $\widehat{k_\tau}$, to deviate from the corresponding Bayesian posterior k_τ. As explained in the main text, we assume that there exists some $\beta \geq 0$ such that

$$\widehat{k_\tau} = \beta \cdot k_\tau \tag{C.2}$$

Second, for each information environment τ, it allows voters' perceived pivotal probabilities, $\widehat{PivA}_\tau$ and $\widehat{PivB}_\tau$, to deviate from their actual values. More specifically, we assume that there exists a $\rho \in [0,1]$ such that

$$\widehat{PivA}_\tau = \rho \cdot PivA_\tau + (1-\rho) \cdot \overline{PivA} \tag{C.3}$$

$$\widehat{PivB}_\tau = \rho \cdot PivB_\tau + (1-\rho) \cdot \overline{PivB} \tag{C.4}$$

In (C.3) and (C.4), $Piv\Omega_\tau$ is the actual pivotal probability of a vote for candidate $\Omega \in \{A,B\}$ in equilibrium, which is derived below. $\overline{Piv\Omega} = \sum_{\tau\in\Gamma} f_\tau \cdot Piv\Omega_\tau$ for $\Omega \in \{A,B\}$, where f_τ denotes the expected frequency of encountering each information environment τ.[6] If $\rho = 0$, voters mistakenly believe that the probabilities of casting pivotal votes are constant across all information environments, but they correctly estimate these pivotal probabilities on average. If $\rho = 1$, voters precisely infer pivotal probabilities in each information environment, as in standard BNE and QRE. With $\rho \in (0,1)$, voters partly realize the relationship between pivotal probabilities and the information environment, but insufficiently so compared to a rational agent.

Notice that both non-Bayesian updating and partial competition neglect can affect a voter's

[6] In our experiment, these frequencies are $f_{NoInfo} = \frac{1}{4}$, $f_{(UB_A,A)} = f_{(UB_A,B)} = \frac{1}{4} \cdot \frac{1}{2} = \frac{1}{8}$, $f_{(WB_A,A)} = \frac{1}{4} \cdot \frac{3}{4} = \frac{3}{16}$, $f_{(WB_A,B)} = \frac{1}{4} \cdot \frac{1}{4} = \frac{1}{16}$, $f_{(SB_A,A)} = \frac{1}{4} \cdot \frac{19}{20} = \frac{19}{80}$ and $f_{(SB_A,B)} = \frac{1}{4} \cdot \frac{1}{80} = \frac{1}{320}$.

judgement about the expected utility from voting. Contrary to (A.5) and (A.6), in our hybrid equilibrium model any voter *i*'s expected utilities from voting for A and B are

$$\widehat{EU^A}(\tau, v_i, c_i) = \frac{(\widehat{k_\tau} + v_i) \cdot \widehat{PivA}_\tau - c_i}{100} \tag{C.5}$$

$$\widehat{EU^B}(\tau, v_i, c_i) = \frac{-(\widehat{k_\tau} + v_i) \cdot \widehat{PivB}_\tau - c_i}{100} \tag{C.6}$$

When $\beta = \rho = 1$, $\widehat{EU^A}(\tau, v_i, c_i)$ and $\widehat{EU^B}(\tau, v_i, c_i)$ are equivalent to, respectively, (A.5) and (A.6) formulated in Appendix A.2.

Finally, our hybrid model allows voters to display distinct levels of rationality for candidate choice and turnout decisions. We model this by an extensive form version of our election game, where voters are assumed to adopt a two-stage decision-making process. At the first stage (S1), voter *i* decides whether to vote or to abstain. If she decides to vote in S1, then the game moves to the second stage (S2), where the voter has to decide which candidate to vote for. We allow voters to possess distinct noise parameters for decisions at different stages. Let λ_t and λ_p denote the noise parameters for stage S1 (turnout decision) and S2 (candidate choice), respectively. In the spirit of McKelvey and Palfrey (1998), we derive the logit *agent quantal response equilibrium* (AQRE) for this extensive version of our election game.[7] We do so by backward induction. In S2 (i.e., conditional on turnout), voter *i* can only choose between candidate A and B. In the logit AQRE, these choice probabilities are given by

$$p^A(\tau, v_i, c_i; \lambda_p) = \frac{e^{\lambda_p EU^A(\tau, v_i, c_i)}}{e^{\lambda_p EU^A(\tau, v_i, c_i)} + e^{\lambda_p EU^B(\tau, v_i, c_i)}} \tag{C.7}$$

$$p^B(\tau, v_i, c_i; \lambda_p) = \frac{e^{\lambda_p EU^B(\tau, v_i, c_i)}}{e^{\lambda_p EU^A(\tau, v_i, c_i)} + e^{\lambda_p EU^A(\tau, v_i, c_i)}} \tag{C.8}$$

Voter *i*'s expected utility from voting is then

$$EU^{Vote}(\tau, v_i, c_i; \lambda_p) = p^A(\tau, v_i, c_i; \lambda_p) \cdot EU^A(\tau, v_i, c_i) + p^B(\tau, v_i, c_i; \lambda_p) \cdot EU^A(\tau, v_i, c_i) \tag{C.9}$$

[7] We also estimated another type of extensive form AQRE model where voters at the first stage S1 decide which candidate to support, and at the second stage S2 decide whether to abstain or to vote for the candidate they choose to support in S1. Using Vuong's closeness tests (Vuong, 1989), we find that this model is outperformed by the current AQRE model presented in this appendix.

In S1, the voter's probabilities to vote (p^T) and to abstain (p^O) are

$$p^T(\tau, v_i, c_i; \lambda_p, \lambda_t) = \frac{e^{\lambda_t EU^{Vote}(\tau, v_i, c_i; \lambda_p)}}{e^{\lambda_t EU^{Vote}(\tau, v_i, c_i; \lambda_p)} + 1} \tag{C.10}$$

$$p^O(\tau, v_i, c_i; \lambda_p, \lambda_t) = \frac{1}{e^{\lambda_t EU^{Vote}(\tau, v_i, c_i; \lambda_p)} + 1} \tag{C.11}$$

Therefore, *a priori* the probabilities that voter i votes for candidate A and B are

$$p^A(\tau, v_i, c_i; \lambda_p, \lambda_t) = p^T(\tau, v_i, c_i; \lambda_p, \lambda_t) \cdot p^A(\tau, v_i, c_i; \lambda_p) \tag{C.12}$$

$$p^B(\tau, v_i, c_i; \lambda_p, \lambda_t) = p^T(\tau, v_i, c_i; \lambda_p, \lambda_t) \cdot p^B(\tau, v_i, c_i; \lambda_p) \tag{C.13}$$

Akin to the derivation of QRE in Appendix A.2, let $\mathbb{P}^d(\tau; \lambda)$ be a $6 \times C$ matrix with its (r, s) element $\mathbb{P}^d_{r,s}(\tau; \lambda) = p^d(\widehat{k_\tau}, v^r, c^s; \lambda)$, for all $d \in \{A, B, O\}$.[8] Following the same logic under (A.10) to (A.11) in Appendix A.2, we can derive for this two-stage AQRE model the probabilities of a randomly sampled voter voting for A and B, respectively, in information environment τ by

$$q^A(\tau; \lambda_p, \lambda_t) = \frac{1}{6} \times \frac{1}{C} \cdot \vec{e}_{1\times 6} \cdot \mathbb{P}^A(\tau; \lambda_p, \lambda_t) \cdot \vec{e}_{C\times 1} \tag{C.14}$$

$$q^B(\tau; \lambda_p, \lambda_t) = \frac{1}{6} \times \frac{1}{C} \cdot \vec{e}_{1\times 6} \cdot \mathbb{P}^B(\tau; \lambda_p, \lambda_t) \cdot \vec{e}_{C\times 1} \tag{C.15}$$

Finally, the pivotal probabilities $PivA_\tau$ and $PivB_\tau$ can be obtained from equations (A.1) and (A.2) by replacing q_d with $q^d(\tau; \lambda_p, \lambda_t)$ for $d \in \{A, B, O\}$:

$$\begin{aligned} PivA_\tau =& \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i} \binom{\mathscr{N} - i}{i} q^A(\tau; \lambda_p, \lambda_t)^i q^B(\tau; \lambda_p, \lambda_t)^i q^O(\tau; \lambda_p, \lambda_t)^{\mathscr{N}-1-2i} \\ &+ \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i} \binom{\mathscr{N} - i}{i+1} q^A(\tau; \lambda_p, \lambda_t)^i q^B(\tau; \lambda_p, \lambda_t)^{i+1} q^O(\tau; \lambda_p, \lambda_t)^{\mathscr{N}-1-2i} \end{aligned} \tag{C.16}$$

$$\begin{aligned} PivB_\tau =& \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i} \binom{\mathscr{N} - i}{i} q^A(\tau; \lambda_p, \lambda_t)^i q^B(\tau; \lambda_p, \lambda_t)^i q^O(\tau; \lambda_p, \lambda_t)^{\mathscr{N}-1-2i} \\ &+ \frac{1}{2} \sum_{i=0}^{\lfloor \frac{\mathscr{N}}{2} \rfloor} \binom{\mathscr{N}}{i} \binom{\mathscr{N} - i}{i+1} q^A(\tau; \lambda_p, \lambda_t)^{i+1} q^B(\tau; \lambda_p, \lambda_t)^i q^O(\tau; \lambda_p, \lambda_t)^{\mathscr{N}-1-2i} \end{aligned} \tag{C.17}$$

Equations (C.1) to (C.17) formulate a fixed-point problem that we can numerically solve for any given set of model parameters $\{\lambda_t, \lambda_p, \beta, \rho\}$.

[8] Recall from Appendix A.2 that v^r denotes the r'th element of set $\{-100, -50, -20, 20, 50, 100\}$ and c^s denotes the s'th element of set $\{1, 2, \cdots, 15\}$.

C.2 Estimation Methods

Each of the models above predicts a set of decision probabilities $p^d(k,v,c|\Lambda)$ for each decision $d \in \{A,B,O\}$, conditional on (k,v,c) and the set of parameter(s) Λ. Λ equals $\{\lambda_p, \lambda_t, \beta, \rho\}$ for models concerning the distinct levels of rationality, while it equals $\{\lambda, \beta, \rho\}$ for models excluding this mechanism. Moreover, models excluding non-Bayesian updating and competition neglect assume $\beta = 1$ and $\rho = 1$, respectively. We use the maximum likelihood (ML) method to estimate the model parameters. The log likelihood function aggregates voting decisions in each election by each individual, and it is given by

$$\mathscr{L}_N(\Lambda) = \sum_{i=1}^{N} \sum_{t=1}^{T} \ln p^{d_{it}}(k_t, v_{it}, c_{it}|\Lambda) \tag{C.18}$$

where i is the index for individual subjects and t is the index for elections.

Let $\Theta \equiv \{(k,v,c)|\exists i,t \text{ such that } (k,v,c) = (k_t, v_{it}, c_{it})\}$ be the set of all combinations of (k,v,c) that appeared in the experiment and let N_θ be the number of observations for any $\theta \in \Theta$. Moreover, let f_θ^d denote the observed frequency of decision $d \in \{A,B,O\}$ for each $\theta \in \Theta$. We can then rewrite (C.18) in a more compact way as

$$\mathscr{L}_N(\Lambda) = \sum_{\theta \in \Theta} \left(N_\theta \cdot \sum_{d \in \{A,B,O\}} f_\theta^d \cdot \ln p^d(\theta|\Lambda) \right) \tag{C.19}$$

The maximum likelihood estimator (MLE) is then given by the maximizer of function (C.19). We denote the obtained MLE by $\widehat{\Lambda}$. The maximal log likelihood then equals $\mathscr{L}_N(\widehat{\Lambda})$. We construct a "fitting score" to measure the performance of the hybrid models in a range between 0% to 100% using the approach from Goeree, Louis and Zhang (2018). Specifically, we compare $\mathscr{L}_N(\widehat{\Lambda})$ to an upper bound $\overline{\mathscr{L}_N}$ and a lower bound $\underline{\mathscr{L}_N}$, which are constructed as follows:

$$\overline{\mathscr{L}_N} \equiv \sum_{\theta \in \Theta} \left(N_\theta \cdot \sum_{d \in \{A,B,O\}} f_\theta^d \cdot \ln f_\theta^d \right)$$

$$\underline{\mathscr{L}_N} \equiv \sum_{\theta \in \Theta} \left(N_\theta \cdot \sum_{d \in \{A,B,O\}} f_\theta^d \cdot \ln \frac{1}{3} \right) = -N \ln 3$$

The upper bound $\overline{\mathscr{L}_N}$ is obtained by setting the predicted choice probabilities exactly equal to the observed frequencies, which yields a global maximum of the log likelihood function. Hence, $\mathscr{L}_N(\widehat{\Lambda}) \leq \overline{\mathscr{L}_N}$ holds generically. The lower bound $\underline{\mathscr{L}_N}$ is obtained by assuming that voters just decide in a uniformly random manner, making each choice with probability one third regardless of (k,v,c). In principle, $\mathscr{L}_N(\widehat{\Lambda})$ could be lower than $\underline{\mathscr{L}_N}$; this would suggest that $\widehat{\Lambda}$ performs even worse than a purely random choice model.[9] The fitting score is then constructed as

$$R_{MLE}(\widehat{\Lambda}) = \frac{\mathscr{L}_N(\widehat{\Lambda}) - \underline{\mathscr{L}_N}}{\overline{\mathscr{L}_N} - \underline{\mathscr{L}_N}} \tag{C.20}$$

$R_{MLE}(\widehat{\Lambda})$ is a linear transformation of $\mathscr{L}_N(\widehat{\Lambda})$ to a zero-one scale, provided that $\mathscr{L}_N(\widehat{\Lambda}) \geq \underline{\mathscr{L}_N}$. The estimation results for our experiment conducted in 2017 is summarized in Table 2 of the main text.

[9] In the standard QRE model presented in Appendix A.2, $\mathscr{L}_N(\widehat{\Lambda}) < \underline{\mathscr{L}_N}$ is impossible because the random choice model is nested by setting $\lambda = 0$. In the two-stage AQRE model, however, a random choice model might perform better because it is not nested; no pairs of (λ_t, λ_p) can generate uniformly random choices. To see this, note that even by setting $\lambda_t = \lambda_p = 0$, a voter would abstain with probability $\frac{1}{2}$ and vote for each candidate with probability $\frac{1}{4}$, which is different from a uniform distribution.

D Instructions and Sample Screen Shots

[In this section we reproduce the instructions for subjects in sessions with $|M| = 1$. While reading instructions, subjects were free to refer to previous pages. Below we provide the exact texts for the main instructions, instructions for the belief elicitation tasks and post-experiment questionnaire, respectively.][10]

[Instruction, control questions and a short summary]

Welcome to the experiment! [Screen 0]

Thank you for participating in this experiment on group decision making. In this experiment, you can earn money. The amount of money you earn depends on the decisions you and the other participants make and on random events.

Before the experiment starts you will receive detailed instructions. These instructions are simple, and if you follow them carefully you may earn a considerable amount of money. The money will be paid to you in cash at the end of the experiment. We ensure that your final earnings remain confidential: we will not inform other participants of your final earnings. All of your decisions will be recorded anonymously. Nobody will be able to link any specific decisions to your name.

In today's experiment you can earn "tokens". The conversion rate is such that 50 tokens = 1€, so for each token you receive 2 eurocents. On top of this you will receive a participation fee of 10€.

During the experiment, please do not communicate with other participants. If you have any questions, please raise your hand and the experimenter will come to your table to answer your questions in private.

[10] Comments within brackets "[]" were not included in the instructions.

Elections, Groups, and Vases [Screen 1]

This experiment consists of a series of elections. In each election, there are 25 voters, including you and the other 24 participants. There are two candidates in each election. These are represented by two vases, **A** and **B** (see Figure 1). In each election, all voters will be randomly assigned to either team **A** or team **B**. Each voter is equally likely to be assigned to either team. Assignment to a team is important, because you will receive a bonus if your team wins the election. This is explained next.

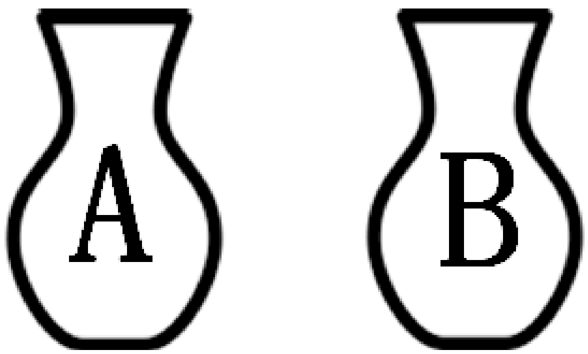


Figure 1: Two candidate vases, **A** and **B**

Bonus [Screen 2]

A voter will gain a bonus of X tokens if the vase belonging to his/her team wins the election. Thus, if you are in team **A**, you will gain a bonus of X tokens if vase **A** is elected, but no bonus if vase **B** is elected. Similarly, if you are in team **B**, you will gain a bonus of X tokens if vase B is elected, and no bonus if vase A is elected.

The size of the bonus X will be independently drawn for each voter. It equals either 20, 50, or 100 tokens. Each of these values is equally likely. Which team you are in and the size of your bonus is determined independently from other voters, and will differ from one election to another. In each election, you will be told your team and the size of the bonus X before you make your voting decision.

Additional earnings: Diamonds [Screen 3]

Aside from making money from the bonus, you can also earn money if the vase that was chosen contains so-called "diamonds". This works as follows.

At the beginning of each election, the computer will randomly select (with equal probability) one of the two vases and fill it with k "diamonds" (see Figure 2).

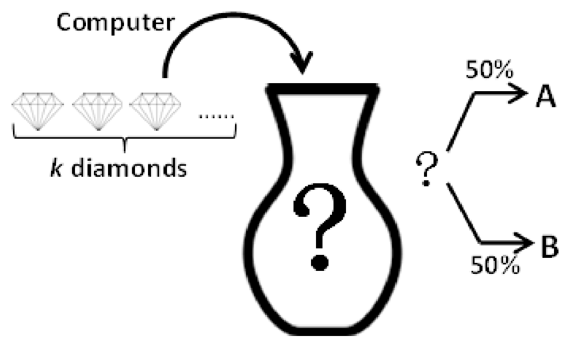


Figure 2: One random vase filled with k "diamonds"

The number of diamonds k is randomly determined and may change from one election to another. More specifically, k is equally likely to be 10, 20, 30, 40, 50, 60, 70, 80, 90, or 100 (so any multiple of 10 between 10 and 100). The other vase gets no diamonds. If the vase containing the diamonds wins the election, all voters will gain these k diamonds as tokens (so each diamond is worth one token).

In each election, the computer will independently determine which vase to fill as well as with how many diamonds. Therefore, which vase contains diamonds, and how many diamonds there are, will likely change from one election to another. You will never be directly informed about which vase has been filled and how many diamonds it contains.

Voting for a vase [Screen 4]

In each election, you have to decide whether or not to vote, and if so, for which vase. If you decide to vote, you pay a voting cost, which is equally likely to be 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, or 15 tokens (so any integer between 1 and 15). These voting costs are drawn independently across voters as well as across elections. Therefore, your voting costs are unrelated to those of other voters and may differ from election to election.

To recap: Before making your voting decision, you will be informed of which team you are in, the size of your bonus X, and your own voting costs. You will not know other voters' team, bonus or costs, nor will you receive any direct information about the allocation of diamonds.

After all voters have made their decisions, the election outcome will be determined by majority rule: the vase that obtains more votes wins the election. If there is a tie, the computer will randomly determine the winning vase by a coin toss.

Earnings [Screen 5]

Your earnings from an election are as follows:

$$\begin{aligned} \text{Earning } &= \text{bonus } X \text{ (if the winning vase belongs to your team)} \\ &+ \text{number of diamonds in the winning vase } - \text{voting costs (if you vote)} \end{aligned}$$

For example, suppose that in an election the computer chooses vase **B** and fills it with 40 diamonds. You are in team **A** with a bonus size of $X = 50$, and your voting costs equal 7. You decide to vote for vase **A**. The outcome of the election reveals that 7 voters vote for **A**, 8 voters vote for **B**, while all the remaining voters abstain. Vase **B** thus wins the election because it has more votes than **A**. Your earnings then equal:

$$0 + 40 - 7 = 33 \text{ tokens}$$

You do not get your bonus $X = 50$ tokens since the winning vase (**B**) does not belong to your team (**A**). The amount of 40 comes from the value of the diamonds in the winning vase (**B**). Finally, you pay a cost of 7 tokens since you decided to cast a vote.

Information about diamonds [Screen 6]

As already noted, you will never be directly informed about which vase is filled and how many diamonds it contains. However, you may receive **indirect** information about this from a “robot”. The robot knows which vase was chosen and with how many diamonds it was filled.

In some elections, a robot may provide public information about the diamonds. It does so by sending either message **A** or message **B** to all voters (so all voters get the same message).

The robot comes in three different types: ALPHA, BETA, and GAMMA. These types use different strategies to determine what message to send. More specifically:

- ALPHA sends message **A** if vase **A** contains any diamonds, and message **B** if vase **B** contains any diamonds.

- BETA sends message **A** if vase **B** contains 50 diamonds or fewer, and message **B** if vase **B** contains 60 diamonds or more.

- GAMMA sends message **A** if vase **B** contains 90 diamonds or fewer, and message **B** only if vase **B** contains 100 diamonds.

In some elections, the robot will be type ALPHA, in some it will be type BETA and in some it will be type GAMMA. Aside from one of these robot types, in some elections there may be no robot at all. In that case no information about the allocation of diamonds is provided.

The table below summarizes the indirect information you (and all other voters) will receive in different cases. This table will also be given to you in a printed handout. The table shows 20 different situations that may occur. Because both vases are equally likely to be chosen and the number of diamonds is equally likely to be any multiple of 10 between 10 and 100, all of these twenty situations are equally likely to occur in any given election.

	# of diamonds in vase **A**	# of diamonds in vase **B**	No Robot	ALPHA	BETA	GAMMA
1	100	0	-	A	A	A
2	90	0	-	A	A	A
3	80	0	-	A	A	A
4	70	0	-	A	A	A
5	60	0	-	A	A	A
6	50	0	-	A	A	A
7	40	0	-	A	A	A
8	30	0	-	A	A	A
9	20	0	-	A	A	A
10	10	0	-	A	A	A
11	0	10	-	B	A	A
12	0	20	-	B	A	A
13	0	30	-	B	A	A
14	0	40	-	B	A	A
15	0	50	-	B	A	A
16	0	60	-	B	B	A
17	0	70	-	B	B	A
18	0	80	-	B	B	A
19	0	90	-	B	B	A
20	0	100	-	B	B	B

Note: The cells marked Red indicate cases where the robot sends message **A**, while the cells marked Blue indicate cases where the robot sends message **B**.

Elections in "blocks" [Screen 7]

The experiment consists of **12 blocks**, each containing **8 elections**. This makes **96 elections** in total.

In each block, one of the four scenarios "No Robot", "robot ALPHA", "robot BETA", or "robot GAMMA" applies. At the beginning of each block you are informed about the scenario that applies in that block. This means that at the start of each block we will tell you which robot (if any) will send messages in the 8 elections in this block.

In elections without a robot, you are directly asked to make voting decisions without any information about diamonds allocation. In elections with a robot providing information, the voting procedure works as follows.

Before receiving the actual message sent by that robot, you are asked to make voting decisions for each possible message. Specifically, you will be asked:

- What would be your voting decision if robot T sends message **A**?
- What would be your voting decision if robot T sends message **B**?

where we replace 'T' by either 'ALPHA', 'BETA' or 'GAMMA'. For each question, you have to make a decision among voting for vase **A**, voting for vase **B**, or abstaining. After all participants have made their decisions, the message actually sent by the robot will be revealed and all participants' corresponding voting decisions for that message will be carried out to determine the outcome for that election.

Overall payment [Screen 8]

At the end of the experiment, we will randomly choose one election from each block to calculate your earnings from elections.

In addition, before the last election in each block with a robot, we will invite you to make an estimate that gives you a chance to win a potential prize of 10 €in a lottery. You will receive instructions for these estimation tasks when you get there. We will randomly choose one of these estimation tasks for payment. The election where the estimation task is chosen will NOT belong to the elections selected to calculate your election earnings. This means that you cannot get both election earnings and the lottery prize from the same election.

Therefore, your overall payment consists of your participation fee (10 €), the earnings from 12 randomly selected elections (one from each block), and a prize of 10 €if you win the lottery belonging to the randomly selected estimation task. There are no training elections, so you start deciding for money from the very beginning.

[Screen 9: Control Questions, with correct answers in red]

To check your understanding of these instructions, please answer the following questions:

Question 1. [True/False] Each election consists of 25 voters. You will play all the elections in this experiment with the same group of participants.	[True]	[False]
Question 2: [True/False] It is possible that vase A contains 30 diamonds while vase B contains 60 diamonds in the same election.	[True]	[False]
Question 3: [True/False] Vase A is more likely to contain any diamonds than vase B.	[True]	[False]
Question 4: [True/False] Every voter is equally likely to be assigned to either team A or team B. Which team you will be assigned to has nothing to do with others.	[True]	[False]
Question 5: [True/False] If the winning vase belongs to your team, you will gain a bonus of X tokens. X is equally likely to be 20, 50, or 100 tokens. The size of your bonus may be different from those of others.	[True]	[False]
Question 6: [True/False] If you decide to vote, you have to pay a voting cost, which is equally likely to be any integer between 1 and 15 tokens. Your voting costs may be different from those of others.	[True]	[False]
Question 7: [True/False] You are informed about which vase contains diamonds and how many diamonds are there before an election starts.	[True]	[False]
Question 8: [True/False] If there is a robot providing information about diamonds allocation, all voters will receive the message sent by the robot.	[True]	[False]
Question 9: [True/False] If robot BETA sends message A, it is possible that vase A contains no diamonds at all.	[True]	[False]
Question 10: Suppose that in an election vase A contains no diamonds, and vase B contains 90 diamonds. What message will robot GAMMA send to all voters?	[A]	[B]

Question 11: Suppose that in an election vase A contains 50 diamonds. You are in team A, and the size of your bonus is 50. Your voting costs equal 10 and you decide to abstain. The election outcome is such that there are 8 voters voting for A, 5 voters voting for B, while the remaining 12 voters abstain. What are your earnings in this election, in terms of tokens? [100] tokens.

Summary [Screen 10, also distributed in printed handout]

Electorate of 25 voters: In this experiment, you will play a series of elections, with a group of 25 voters. You will be matched with the remaining 24 other participants to form the election group, and play all the elections with the **same** group of participants.

Team assignment: In each election, you are equally likely to be assigned to team **A** or to team **B**. You will gain an individual bonus if the winning vase belongs to your team.

Bonus: The size of the bonus is equally likely to be **20, 50 or 100 tokens**, and is determined independently for each voter. So the size of your bonus will likely be different from others.

Diamonds: In each election, each vase is equally likely to contain some diamonds. The number of diamonds is equally likely to be **any multiple of 10 between 10 and 100 tokens**. If the vase containing diamonds wins the election, each voter obtains all the diamonds in it.

Voting: As a voter, you can choose to vote for either vase, or to abstain. If you decide to vote, you will pay a voting cost, which is equally likely to be **any integer between 1 and 15 tokens**. Your voting costs may be different from others.

Election rule: The vase with the higher number of votes wins the election. If there is a tie, the winning vase will be determined by a coin toss, so either vase wins with probability 50%.

Information from "robots": You will not be directly informed about the allocation of diamonds. However, one of the three robot types, ALPHA, BETA, and GAMMA, may provide relevant information using the message strategies specified in the handout.

Election in "blocks": The experiment consists of 12 blocks, each containing 8 elections. In each block, there may either be no robot and thus no information about the diamonds allocation, or one of the three robots types (ALPHA, BETA, GAMMA) will send a public message to all voters before voters make their decisions.

Estimation tasks: Before the last election in each block with robots, we will invite you to make an estimate that gives you a chance to win a potential prize of 10 €in a lottery. We will randomly choose one of these estimation tasks for payment. You will receive instructions for these estimation tasks when you get there.

Overall payment: Your overall payment consists of your participation fee (10 €), the earnings from 12 randomly selected elections (one from each block), as well as a prize of 10 €if you win the lottery belonging to the randomly selected estimation task. The random selection is such that the paid estimation task does NOT belong to one of the 12 selected elections.

[Instructions for the estimation task (treatment WB_A under $|M| = 1$)]

Estimation task (with potential prize 10 €)

Before the next election starts, we kindly ask you to estimate how likely it is that vase **A** pays *strictly* more to you than vase **B**, depending on the messages sent by robot BETA. Vase **A** pays you strictly more than vase **B** if you can earn more money (without considering voting cost) under the victory of vase **A** than under the victory of vase **B**. *If both vases give the same amount, Vase **A** does not give you strictly more than Vase **B***. For example, suppose you are in team **B**, with a bonus size of 20 tokens. Then vase **A** pays you strictly more than vase **B** only if vase **A** contains 30 diamonds or more. This is because you can earn at least 30 tokens under the victory of vase **A**, while only 20 tokens under the victory of vase **B**. *Note that whether vase **A** pays you strictly more than vase **B** does not depend on whether you vote or not, nor does it depend on the actual election outcome.*

Depending on your answers, you may win a prize of 10 €in a lottery. Specifically, you will be asked to make choices by filling out the 3 lists below: (These are sample lists for illustrations, so please do not fill them out now)

This list asks you to assess the chance that vase **A** pays you strictly more than vase **B** when robot BETA sends message **A**.

How likely do you think that vase **A** pays you strictly more than vase **B**, if robot **BETA** sends message **A**?				
	Option 1	**Which option do you prefer?**		**Option 2**
Choice 1	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 0%
Choice 2	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 5%
Choice 3	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 10%
Choice 4	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 15%
Choice 5	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 20%
Choice 6	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 25%
Choice 7	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 30%
Choice 8	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 35%
Choice 9	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 40%
Choice 10	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 45%
Choice 11	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 50%
Choice 12	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 55%
Choice 13	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 60%
Choice 14	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 65%
Choice 15	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 70%
Choice 16	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 75%
Choice 17	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 80%
Choice 18	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 85%
Choice 19	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 90%
Choice 20	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 95%
Choice 21	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 100%
		OK		

This list asks you to assess the chance that vase **A** pays you strictly more than vase **B** when robot BETA sends message **B**.

How likely do you think that vase **A** pays you strictly more than vase **B**, if robot **BETA** sends message **B**?				
	Option 1	**Which option do you prefer?**		**Option 2**
Choice 1	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 0%
Choice 2	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 5%
Choice 3	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 10%
Choice 4	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 15%
Choice 5	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 20%
Choice 6	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 25%
Choice 7	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 30%
Choice 8	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 35%
Choice 9	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 40%
Choice 10	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 45%
Choice 11	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 50%
Choice 12	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 55%
Choice 13	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 60%
Choice 14	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 65%
Choice 15	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 70%
Choice 16	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 75%
Choice 17	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 80%
Choice 18	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 85%
Choice 19	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 90%
Choice 20	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 95%
Choice 21	Win10€ if vase **A** pays strictly more to you than vase **B**	○	○	Win10€ with probability 100%
		OK		

Only one of the lists you fill out will be used to determine your participation in the lottery. Which list is chosen depends on the actual message robot BETA sends in this election. If the robot sends message **A**, then the first list will be used. If it sends message **B** then the second list will be used. One of the 21 choices from the chosen list will be randomly selected to determine the lottery you will take part in.

So how should you decide which options to tick? That depends on how likely you think it is that vase **A** will pay you strictly more than vase **B**, depending on the message sent by robot BETA. For instance, suppose you think that there is a 63% chance that vase **A** will pay you strictly more. If you want to have the highest chance of winning the 10 €prize, then you should tick **Option 1** on any choice where **Option 2** offers you less than a 63% chance of winning the prize, and you should tick **Option 2** on any choice where the **Option 2** offers you a greater than 63% chance of winning the prize. *Our payment procedure is designed such that your expected earnings are highest if you provide your most accurate estimate.*

You will be asked to do the same estimation task in the last election of every block where robots are providing information. At the end of the experiment one of these estimation tasks will be randomly selected for payment. If an election is selected to decide the lottery, then it will not be selected to determine your election earnings. Therefore, you cannot get both election earnings and the lottery prize from the same election.

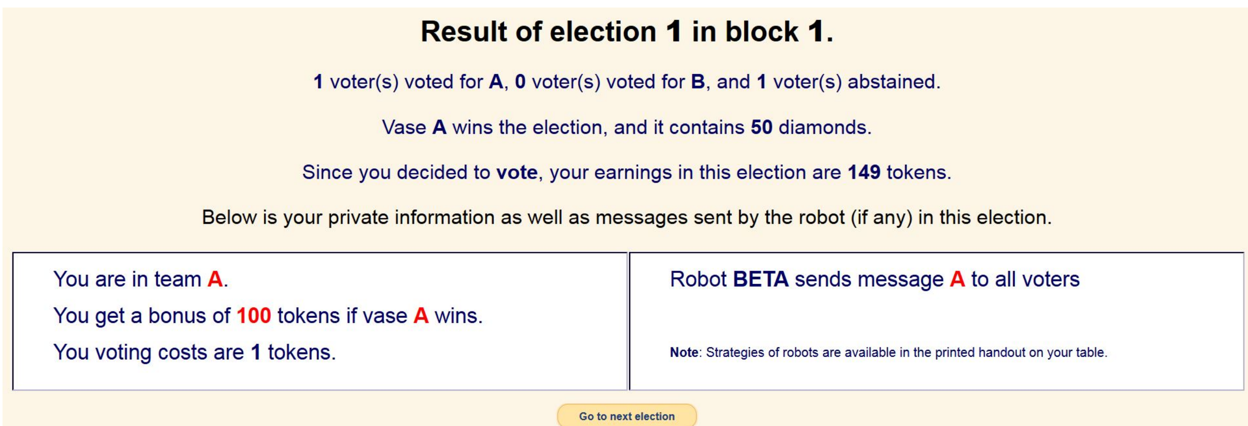
Questionnaire [Post-experiment Questionnaire]

Please fill in this short questionnaire carefully. Your feedback will be very helpful for our analysis. Thank you!

Age:	[Textbox to fill in age]
Gender:	[Radio] Male [Radio] Female
I study at:	[Choose from list]
Please indicate on a scale from 1 (fully disagree) to 7 (fully agree) to what extent you agree with the following statements:	
1. In deciding whether or not to cast a vote, I paid careful attention to the voting costs.	[List: 1 to 7]
2. In deciding whether or not to cast a vote, I paid careful attention to the amount of the individual bonus.	[List: 1 to 7]
3. In the blocks with robots, my decision which vase to vote for depended on the messages of the robots.	[List: 1 to 7]
Please rank how your voting decisions rely on the messages from robots in the three scenarios from 1 to 3: (1: rely most; 3: rely least)	1: [List] 2: [List] 3: [List]
Please rank how often do you vote in the four scenarios in the experiment from 1 to 4: (1: most often; 4: least often)	1: [List] 2: [List] 3: [List] 4: [List]
Please rank how competitive do you think the elections are under the four scenarios in the experiment from 1 to 4: (1: most competitive; 4: least competitive) Note: An election is competitive if the vote shares are close for both vases.	1: [List] 2: [List] 3: [List] 4: [List]
Please rank how likely do you think your single vote may change the election outcome under the four scenarios in the experiment from 1 to 4: (1: most likely; 4: least likely)	1: [List] 2: [List] 3: [List] 4: [List]
Did other participants vote more often or less often than you expected? Why?	[(Optional) Textbox here]

[A sample screen shot of the decision interface]

[A sample screen shot of the result interface][11]



[11] The sample result interface is based on a simplified testing program with 2 voters only. In the actual experiment the numbers of voters voting for A, for B and abstaining always sum up to 25, the actual electorate size.

E Electoral Impacts of Endorser Competition

In this appendix we study the electoral impacts of increased competition between endorsers. We do so by increasing the number of endorsers $|M|$ from 1 to 2. For this purpose, we designed and implemented additional experimental sessions with $|M| = 2$ endorsers. For these sessions we introduce an additional endorser which is *weakly B-biased* ($\chi = -55$; WB_B) and labeled as robot "DELTA". Denote the biases of the two endorsers by χ_1 and χ_2, respectively. We consider three treatments with combinations of biases (χ_1, χ_2): $(0, 55)$ (labeled as (UB, WB_A)), $(55, -55)$ (labeled as (WB_A, WB_B)), and $(95, 0)$ (labeled as (SB_A, UB)). In these treatments, voters observe two public messages (one from each endorser). Both endorsers' reporting strategies take the cutoff structure characterized by equation (2) in the main text.

In line with our experiment reported in the main text, for these additional sessions with $|M| = 2$ we also adopted a within-subject design for distinct treatments: $NoInfo$, (UB, WB_A), (WB_A, WB_B), and (SB_A, UB). Other aspects of the experimental design and procedures are also similar; we used the strategy method to elicit voting decisions, applied randomization by blocks to minimize order effect, and elicited voters' beliefs using the choice list approach in the last round of election in each block for treatments other than $NoInfo$.[12] In total six experimental sessions with $|M| = 2$ endorsers were conducted at the CREED laboratory of the University of Amsterdam in the summer of 2017. For each session 25 subjects were recruited. These sessions took on average 200 minutes, and the average payment was about 40.1 euros (with a minimum of 28.2 euros and a maximum of 53.1 euros).[13]

The remainder of this appendix is organized as follows. In subsection E.1 we derive both BNE and QRE predictions for the scenario with $|M| = 2$. Based on these equilibrium analyses, we formulate testable hypotheses concerning the ex-ante impact of introducing a second endorser on election outcomes and voter turnout. The experimental results are subsequently reported in subsection E.2.

E.1 Equilibrium Analyses and Hypotheses

In this subsection we derive BNE and QRE predictions. Let $k_X(\chi_1, \chi_2)$ and $Pr[X|\chi_1, \chi_2]$ denote the posterior expectations of k and the ex-ante probability of sending message combination $X \in \{(A,A), (A,B), (B,B)\}$, respectively, conditional on the endorsers' biases χ_1 and χ_2. Let $\chi_+ \equiv \max\{\chi_1, \chi_2\}$ and $\chi_- \equiv \min\{\chi_1, \chi_2\}$. It follows from the cutoff reporting strategy (cf. equation

[12] Complete instructions for these experimental sessions are available upon request.

[13] Because sessions with $|M| = 2$ took on average 50 minutes longer than sessions with $|M| = 1$, we paid each subject in sessions with $|M| = 2$ an extra amount of 10 euros (unexpected and not pre-announced) at the end of the experiment as a compensation.

(2) in the main text) that

$$Pr[(A,A)|\chi_1,\chi_2] = 1 - F(-\chi_-), \text{ and } k_{(A,A)}(\chi_1,\chi_2) = E[k|k > -\chi_-]$$
$$Pr[(A,B)|\chi_1,\chi_2] = F(-\chi_-) - F(-\chi_+), \text{ and } k_{(A,B)}(\chi_1,\chi_2) = E[k|-\chi_+ < k \leq -\chi_-]$$
$$Pr[(B,B)|\chi_1,\chi_2] = F(-\chi_+), \text{ and } k_{(B,B)}(\chi_1,\chi_2) = E[k|k \leq -\chi_+]$$

Following the logic of Appendix A, conditional on the endorsers' biases (χ_1,χ_2) and realized message combination $X \in \{(A,A),(A,B),(B,B)\}$, both BNE and QRE predictions can be obtained by replacing k by the corresponding posterior expectation $k_X(\chi_1,\chi_2)$. Table E.1 summarizes all $Pr[X|\chi_1,\chi_2]$, $k_X(\chi_1,\chi_2)$, and both the interim and ex-ante outcomes predicted by BNE and QRE for all combinations of (χ_1,χ_2).

Table E.1: Rational Posterior Expectations of k and Theoretical Predictions under $|M| = 2$

Endorsers' Biases (χ_1,χ_2)	$(0,55)$			$(55,-55)$			$(95,0)$		
Message Combination X	(A,A)	(A,B)	(B,B)	(A,A)	(A,B)	(B,B)	(A,A)	(A,B)	(B,B)
$Pr[X\|\chi_1,\chi_2]$	0.50	0.25	0.25	0.25	0.50	0.25	0.50	0.45	0.05
$k_X(\chi_1,\chi_2)$	55	−30	−80	80	0	−80	55	−50	−100
BNE predictions									
Expected vote share of A	0.81	0.32	0.10	0.90	0.50	0.10	0.81	0.21	0.00
Winning probability of A	0.94	0.15	0.03	0.97	0.50	0.03	0.94	0.07	0.02
Expected voter turnout	0.22	0.32	0.17	0.17	0.45	0.17	0.22	0.23	0.13
QRE predictions									
Expected vote share of A	0.71	0.36	0.25	0.75	0.50	0.25	0.71	0.30	0.23
Winning probability of A	0.91	0.18	0.06	0.94	0.50	0.06	0.91	0.10	0.04
Expected voter turnout	0.38	0.42	0.37	0.37	0.48	0.37	0.38	0.39	0.36

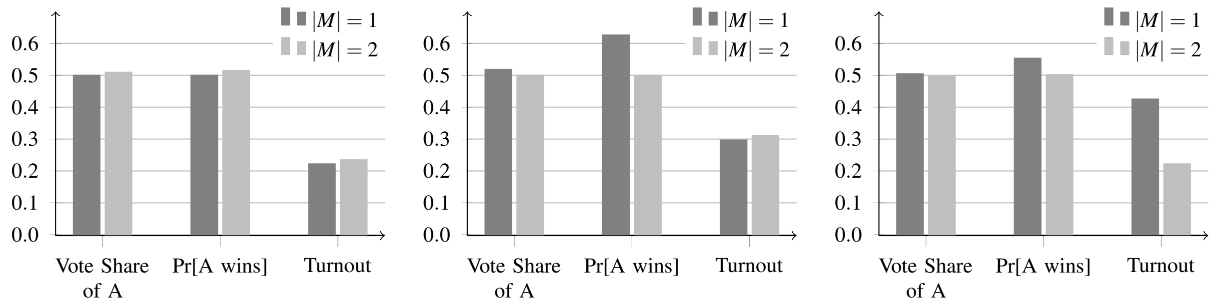
Note: For all (χ_1,χ_2), the law of iterated expectation is satisfied: $\sum_{X\in\{(A,A),(A,B),(B,B)\}} Pr[X|\chi_1,\chi_2]\cdot k_X(\chi_1,\chi_2) = 0$. In generating QRE predictions, we again used the logit response parameter $\widehat{\lambda} = 17.97$ obtained from an out-of-sample estimation based on corresponding sessions in our 2016 experiment.

Using these equilibrium predictions, we study the ex-ante impact of introducing a second endorser on candidates' expected vote shares, the election outcome and voter turnout. As $|M|$ increases from 1 to 2, we denote the biases of the existing and the newly introduced endorsers by χ_1 and χ_2, respectively, and consider the aforementioned three combinations of biases, (UB, WB_A), (WB_A, WB_B) and (SB_A, UB). Given any pair (χ_1,χ_2), we identify the ex-ante electoral impact of introducing a second endorser with bias χ_2 by comparing outcomes from the one-endorser scenario with bias χ_1 to the two-endorser scenario with bias combination (χ_1,χ_2). Figure E.1 presents BNE predictions for these comparisons for candidate A's expected vote share and winning probability, as well as for voter turnout.[14]

[14] QRE predictions are qualitatively similar. More details are available upon request.

Figure E.1: The Electoral Influence of Introducing a Second Endorser

(a) UB versus (UB, WB_A) (b) WB_A versus (WB_A, WB_B) (c) SB_A versus (SB_A, UB)



Note: Panels depict the ex-ante influence, predicted by BNE, of introducing a second endorser on candidate A's expected vote share, winning probability (Pr[A wins]) and voter turnout.

The three panels of Figure E.1 show that introducing a second endorser has very little impact on candidates' expected vote shares from the ex-ante perspective. Regarding the election outcome, we show that introducing a endorser can systematically increase A's winning probability if and only if the second endorser is more A-biased than the existing endorser, i.e., $\chi_2 > \chi_1$. In our election game, this implies that A's ex-ante winning probability increases in the transition from UB to (UB, WB_A), and decreases in the transitions from WB_A to (WB_A, WB_B), and from SB_A to (SB_A, UB). All these predictions are confirmed in Figure E.1. These observations yield Hypothesis E.1.

Hypotheses E.1. *Influence of introducing a second endorser on the election outcome:*

(a) Ex-ante, A's winning probability is higher under (UB, WB_A) than under UB.

(b) Ex-ante, A's winning probability is lower under (WB_A, WB_B) than under WB_A.

(c) Ex-ante, A's winning probability is lower under (SB_A, UB) than under SB_A.

As for voter turnout, Figure E.1 generates three predictions. These are summarized in Hypothesis E.2.

Hypotheses E.2. *Influence of introducing a second endorser on voter turnout:*

(a) Ex-ante, voter turnout is higher under (UB, WB_A) than under UB.

(b) Ex-ante, voter turnout is higher under (WB_A, WB_B) than under WB_A.

(c) Ex-ante, voter turnout is lower under (SB_A, UB) than under SB_A.

E.2 Experimental Results

The aggregate ex-ante electoral impact of introducing a second endorser are presented in Figure E.2. As is evident from the top and middle panels, except for the comparison between SB_A and (SB_A, UB), both BNE and QRE predictions correctly capture, qualitatively and quantitatively, the ex-ante impacts of introducing a second endorser on party vote shares and election outcomes. The bottom panels of Figure E.2 show that, as in sessions with $|M| = 1$, observed turnout rates are rarely affected by the entrance of a second endorser and they are again systematically higher than both BNE and QRE predictions. It is worth noting, however, that these results need not be entirely inconsistent with our theoretical predictions. This is because, except for the comparison between SB_A and (SB_A, UB), the ex-ante impacts of introducing a second endorser on voter turnout predicted by BNE and QRE are both quantitatively negligible.

In what follows we conduct formal statistical tests for Hypotheses E.1 and E.2. Specifically, we use exact Fisher-Pitman permutation tests (henceforth, FPp) for pairwise comparisons of differences in means between sessions with different $|M|$.[15]

Hypothesis E.1a predicts that introducing a weakly A-biased endorser will increase candidate A's ex-ante winning probability, if the preexisting endorser is unbiased. We indeed observe a slight increase in A's winning probability (from 48.3% to 50.7%) in the top-left panel of Figure E.2; the difference is statistically significant (FPp, $p = 0.041$, $N = 12$). Hypothesis E.1b predicts that, if the preexisting endorser is weakly A-biased, then introducing a weakly B-biased endorser will decrease A's winning probability. Indeed, we observe a sizable decrease (from 58.5% to 47.6%) in the top-central panel of Figure E.2, and the difference is statistically significant (FPp, $p = 0.009$, $N = 12$). Finally, Hypothesis E.1c predicts that, if the preexisting endorser is strongly A-biased, then introducing an unbiased endorser will decrease A's winning probability. Again, we observe a sharp decrease (from 66.9% to 52.7%) in the top-central panel of Figure E.2, and the difference is statistically significant (FPp, $p = 0.002$, $N = 12$). Note, however, that given the realized parameter draws for the experiment, both BNE and QRE predictions actually violate Hypothesis E.1c; they predict small treatment effects in the other direction, if any. These findings are summarized in Result E.1.

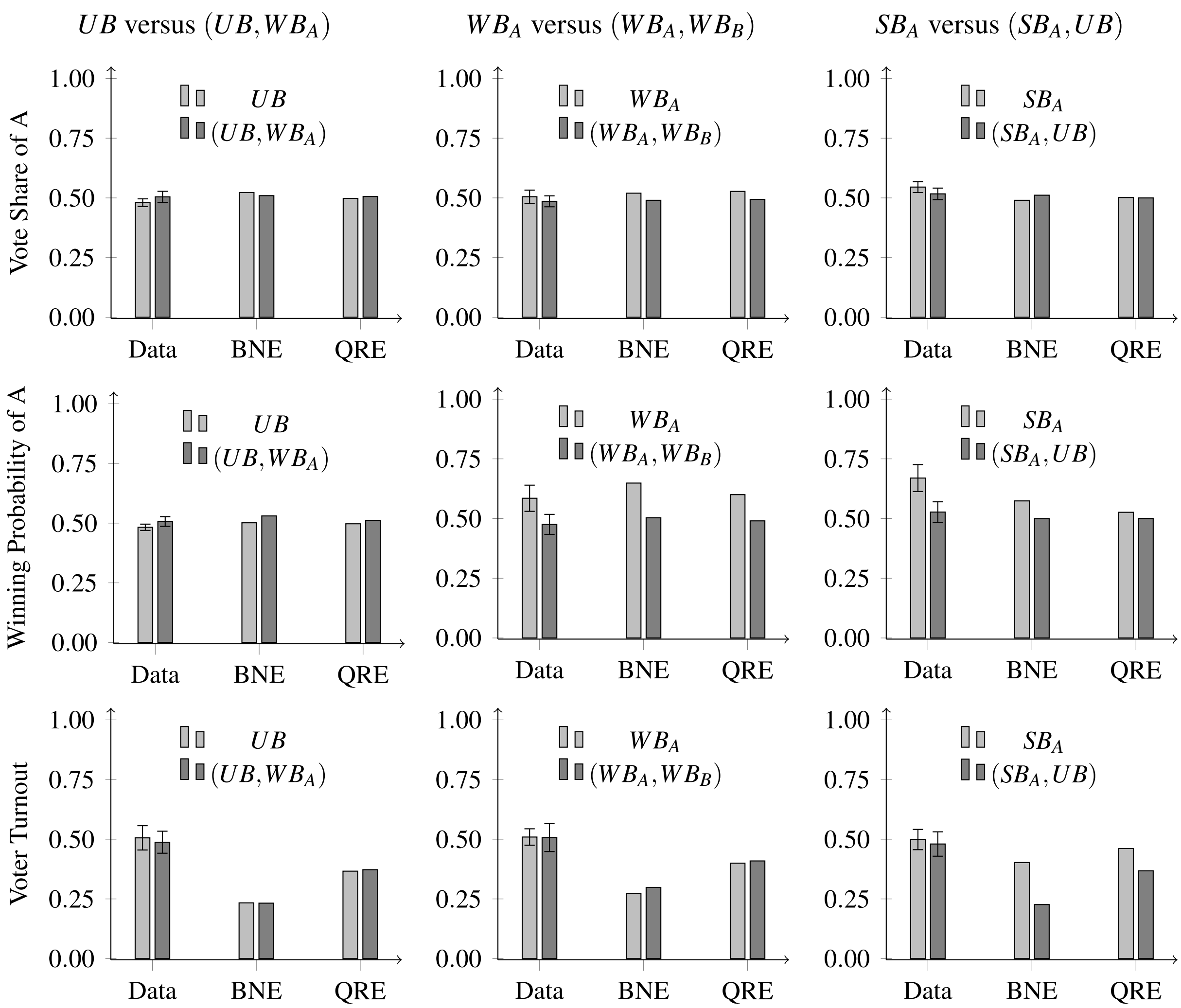
Result E.1. *Influence of introducing a second endorser on candidate A's ex-ante winning probability:*

(a) A's ex-ante winning probability is significantly higher in treatment (UB, WB_A) than in UB.

(b) A's ex-ante winning probability is significantly lower in treatment (WB_A, WB_B) than in WB_A.

[15] Contrary to the statistical tests for sessions with $|M| = 1$ reported in the main text, this is a between-subject comparison because the number of endorsers differs across sessions.

Figure E.2: Ex-ante Electoral Impacts of Introducing a Second Endorser



Note: Bars show candidate A's ex-ante vote share (top panels), winning probability (middle panels), and voter turnout (lower panels) and the corresponding predictions by BNE and QRE. 95% confidence intervals are plotted for the observed outcomes. All theoretical predictions are generated based on the realized parameter draws for the experiment.

(c) *A's ex-ante winning probability is significantly lower in treatment* (SB_A, UB) *than in* SB_A.

Hypothesis E.2a predicts that if the preexisting endorser is unbiased, introducing a biased endorser leads to an increase in voter turnout. Contrary to Hypothesis E.2a, our results (bottom-left panel of Figure E.2) show a slight decrease in turnout (from 50.6% to 48.8%), although this effect is statistically insignificant (FPp, $p = 0.500$, $N = 12$). Hypothesis E.2b predicts that if the preexisting endorser is weakly A-biased, then introducing an weakly B-biased endorser with an identical degree of bias will increase voter turnout. Contrary to HE.2b, ex-ante voter turnout varies little with the presence of an extra endorser (from 50.9% to 50.7%) as shown in the bottom-central panel of Figure E.2. The difference is statistically insignificant (FPp, $p = 0.931$, $N = 12$). Finally, Hypothesis E.2c predicts that if the preexisting endorser is strongly biased (as in SB_A), then introducing an unbiased endorser will decrease voter turnout. Although we indeed observe a slight decrease (from 49.9% to 48.0%, see the bottom-right panel of Figure E.2), this effect is again statistically insignificant (FPp, $p = 0.455$, $N = 12$). Overall, we find no evidence that introducing a second endorser affects voter turnout from the ex-ante perspective. These findings are summarized in Result E.2.

Result E.2. *Influence of introducing a second endorser on voter turnout:*

(a) *Ex-ante, voter turnout does not vary significantly from treatment* UB *to* (UB, WB_A).

(b) *Ex-ante, voter turnout does not vary significantly from treatment* WB_A *to* (WB_A, WB_B).

(c) *Ex-ante, voter turnout does not vary significantly from treatment* SB_A *to* (SB_A, UB).

In a nutshell, we find that introducing a second endorser systematically pushes the election outcome in the direction predicted by theory, yet it has little systematic impact on voter turnout.

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